MULTI-MODEL CONTROL OF A DISTILLATION SYSTEM USING FUZZY RULES

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This paper proposes a multi-model control method based on fuzzy set theory and its application. Fuzzy set theory is provided for unification of the multi-step response models built in various operating points. A control strategy for regulatory control and tracking control can be realized by using these models and the design algorithm of a PID controller. This method was applied to stabilize the distillate component in an ethanol/water distillation system. It was experimentally confirmed that multi-model control using fuzzy rules was an effective method for developing a practical control system for the distillation system.

Introduction

Distillation systems have been widely used for separation processes in the petroleum and chemical industries. Many efforts toward process development and improvement of operation systems for saving energy have been carried out, such as low-reflux operation, multiple-stage columns, heat recovery with a heat pump, etc. Recently, demand has grown for development of an advanced control system in order to realize multipurpose operation, together with the usual stabilizing of product components. The reasons are as follows:

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(a) improvement of saving energy

(b) satisfaction of requirements for higher purity and uniformity of product components

(c) decrease of off-specification products when changing production sequences for various kinds of products

Therefore, many control system design methods for distillation systems have been developed.[2)] But few practical applications have been realized in the field, because:

(1) Dynamic behavior is usually too complicated to be modeled, and even if it is modeled for developing an advanced control system, the model has a small available range for practical use.

(2) **Figure 1** shows a typical schematic diagram of

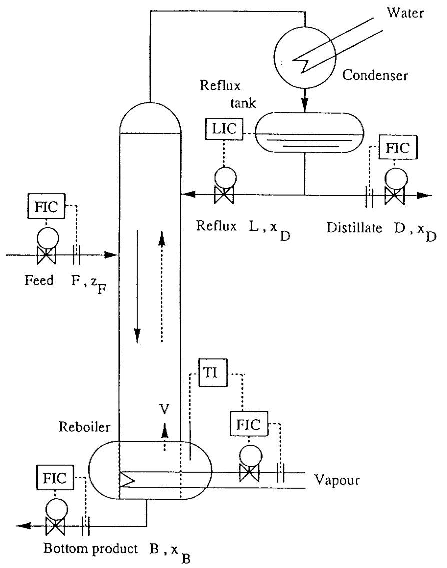

Fig. 1. Schematic diagram of a distillation system with DV configuration

a distillation system with DV configuration, which shows the control system with the volatile component of the top product and the distillate flow rate as the process output and input variables respectively, for example. In general, there are many kinds of couples of the input-output variables in a multi-variable control system, even in a simple binary components distillation system. Optimization can be carried out with respect to a fixed control configuration, but it may be necessary to change the control configuration depending on the control object.

As is well-known, in order to design a control system for a chemical process, its dynamic model must be used effectively. But, in practice, it is often difficult to build a theoretical model because the phenomena in the precess are too complicated to be clearly described. In such a case, we have usually designed a controller based on a response model. Some control theories based on a response model such as regulatory control have been applied to a desired control specification. However, if the specification is widely changed the original control system may not be usable because of lack of usability of the model or nonlinearity of the process dynamics. This fact causes many difficulties in applying conventional control theories to such real problems.

To overcome these difficulties, Binder[1] has proposed a typical multi-model control method in which optimum control at a desired operating point could be determined by unification of the optimum controls calculated from the plural number of process models built at different operating points. Unification is carried out according to the stochastic expectations, which are determined from the error distributions between the calculated values by the models and the observed values.

However, it would be doubtful that the future state of the actual process could be predicted solely from the past data distribution, and that a control strategy obtained only by unification of the optimum controls calculated from these models could guarantee optimum control at various operating points.

On the other hand, with respect to operation of a real process, the gap between theory and realization can be considered to have been compensated by the skilled operators' experience. Fuzzy set theory proposed by Zadeh[5] can be recognized as a practical method to compensate these uncertainties of the process with human knowledge. With fuzzy set theory, such human knowledge can be quantified by using the membership functions and IF THEN rules. This procedure can be considered as a modeling procedure of human understanding of the process dynamics. Process control systems based on fuzzy set theory have recently come into wide use in many fields as an expertized control method that realizes the operators' know-how. But the design algorithm of a fuzzy controller based on a process dynamic model has not been formulated sufficiently. In the field of fuzzy countrol, the idea of using a number of process models constructed at the plural number of operating points has been proposed as fuzzy adaptive control[4]. In this idea, the process model is a fuzzy rule model and the control is determined by interpolation with the controls described in the consequent part of these models. This idea cannot be considered to guarantee also optimum control at the interpolated operating point.

In this paper, a multi-model control approach using fuzzy rules is proposed. Fuzzy rules are provided for synthesizing a process model at an arbitrary operating point by unifying the plural number of process models identified at some determined operating points. Then, to examine the usability of the proposed method, experimental studies are made of stabilizing a component of the top product at the various operating points of a ethanol/water distillation system, where the distillaton column has different dynamics, and on tracking performance in changing the operating point for producing various product specifications.

1. Design of Control System

1.1 Design procedure

The design procedure for the multi-model control system using fuzzy rules proposed in this paper is formulated as follows:

Step 1 Representation of dynamic responses

Step response data of the output variable are respectively acquired at the operating points around the higher and lower purity range of the top product.

Then, the individual transfer functions of the second-order delay with lag time are obtained as Eq. (1).

$$G_p{}^i(S)=K^i\exp(-\tau^iS)/((1+T_1{}^iS)(1+T_2{}^iS)) \quad (i=1,\cdots,\mathrm{I}) \qquad (1)$$

where "I" is the number of operating points, and K^i, $T_1{}^i$, $T_2{}^i$, τ^i are denoted as the proportional gain constant, the time constants and the lag time at the operating point "i" respectively. As the lag term can be rewritten by the Maclaurin expansion, Eq. (1) can be represented in denominator series form as Eq. (2).

$$G_p{}^i(S)=1/(a_0{}^i+a_1{}^iS+a_2{}^iS^2+\cdots) \qquad (2)$$

Step 2 Unification of transfer functions

In this step it is required to determine the transfer function of the process at a certain operating point within the changeable region of a control variable. This procedure is carried out as follows.

First, fuzzy sets $A^i(x_D)$, which define the adaptation region of the parameters of the transfer function $\{a_k{}^i\}$ $(k=1,2,\cdots)$, are prepared. Superscript "i" is the lavel of the fuzzy sets. Second, the model parameters at any other operating point can be obtained from the fuzzy rules as Eq. (3).

$$\text{IF } x_D \text{ is } A^i(x_D) \text{ THEN } a_k=a^*{}_k{}^i \quad (i=1,2,\cdots) \qquad (3)$$

where $a^*{}_k{}^i$ is the parameter value obtained in Step 1. Finally, we can calculate the parameter values a'_k at any operating point $x_D{}^A$ by unifying the value according to the membership values in the premise part of the rules and averaging with weights as Eq. (4):

$$a'_k=\Sigma_{i=1}{}^{\mathrm{I}}\omega^i(A^i(x_D{}^A))\times a^*{}_k{}^i/\Sigma_{i=1}{}^{\mathrm{I}}\omega^i(A^i(x_D{}^A)) \qquad (4)$$

where $\omega^i(A^i(x_D{}^A))$ is the membership value of the fuzzy set $A^i(x_D)$ in $x_D=x_D{}^\wedge$.

Consequently, the transfer function can be obtained at any distillate component value by putting these values into Eq. (5).

$$G(S)=1/(a'_0+a'_1S+a'_2S^2+\cdots) \qquad (5)$$

Step 3 Determination of control parameters

The control parameters can be calculated by Kitamori's design algorithm based on partial knowledge of a process[3] [See Appendix]. With this algorithm we can calculated the control parameters so as to adjust a closed loop response to a desired reference response and tune the PID controller by putting these parameters into the controller.

1.2 Realization

The above-mentioned control system design algorithm can be applied to the following control modes: regulatory control and tacking control.

Mode-1 Regulatory control

The control strategy determined in Steps 1 to 3 can be applied to the tuning of a PID controller at any operating point where there is no properly prepared

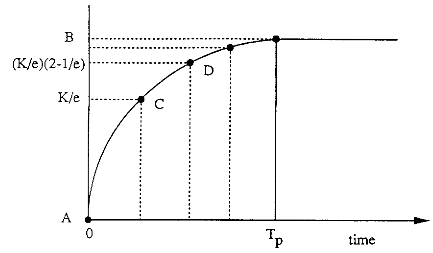

Fig. 2. A reference trajectory and tuning points

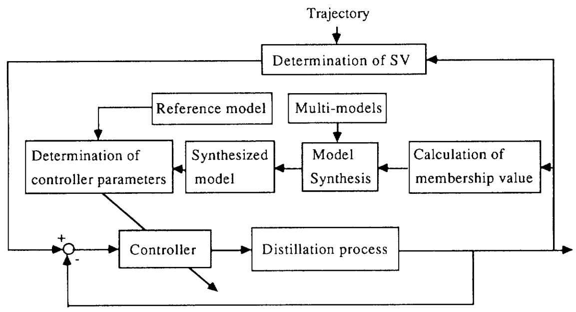

Fig. 3. Schematic diagram of a multi-model control system using fuzzy rules

model. In this case, we can set the parameter values of the PID controller with just the values obtained in Step 3.

Mode-2 Tracking control

The control strategy mentioned above can also be applied to tracking control from an initial operating point to certain final operating point. In this case, we provide the desired trajectory such as shown in **Fig. 2**. Tp in Fig. 2 is the desired time elapsed for movement from the initial operating point A to the final operating point B. The trajectory to be specified is very important from the viewpoint of putting our knowledge into the control strategy. Next, we decide the tuning timing of the PID parameters to reach point B smoothly, such as is shown in Fig. 2. At the initial point A we estimate the parameter values at the next desired point C according to the above algorithm and put them into the PID controller. When the distillate component crosses over point C we evaluate the parameter values at the next operating point D by the algorithm and put them into the controller. Consequently, by repeating this procedure successively we can expect that the distillate components follows the desired trajectory smoothly.

1.3 Configuration of the control system

Figure 3 shows the schematic diagram of a multi-model control system using fuzzy rules realizing the algorithm described above. This system is constituted mainly of two blocks. The first block is provided for synthesizing the process model at the desired operating point by using multi-models and fuzzy reasoning. The second block is provided for determining suitable parameters of the PID controller by using the synthesized model and the reference model. As the controller's pamameters change adaptively, this system can be regarded as a kind of self-tuning regulator system.

2. Experiment

2.1 Experimental apparatus

The distillation column for experiments is 200 mm in diameter and 5000 mm in height. Cascade-mini-rings (DODWELL) are packed to a height of 4000 mm in the middle of the column. The number of theoretical plates of the column corresponds to 11 plates. The ethanol/water mixture (6.3% in ethanol concentration) is fed at the 7th theoretical plate from the top. The reboiler is indirectly heated with steam and a condenser with 4 m^2 heat transfer area is cooled with water. Forty kinds of data measured with sensors, such as temperature, pressure, liquid level, flow rate and liquid density are transfered to the DCS (Distributed Computer System, YEWPACK). The DCS is connected to the SVC (Supervisory Computer System, DG) with LAN as shown in **Fig. 4**. By using this system, the process state can be estimated and the process can be controlled supervisorily. The operators can manage the process only by setting the desirable set point of the tracking trajectory. The parameters of the controllers can be tuned automatically with the proposed algorithm installed in SVC.

Experiments were carried out under the DV configuration with ethanol concentration x_D as the process output variable and with distillate flow rate D as the input variable, as shown in Fig. 1. The step response data of the distillate component x_D, which were measured by a sensor directly, were collected when distillate flow rate D was changed. Control experiments using the PID control system designed by the proposed algorithm were carried out. We selected this configuration for this following reason. By preliminary experiments, the influences of bottom conditions were confirmed to be negligible for evaluating control performance under the experimental conditions adopted. **Table 1** shows the experimental conditions. Cases 1 and 2 show the conditions in the lower-purity range and in the higher-purity range respectively.

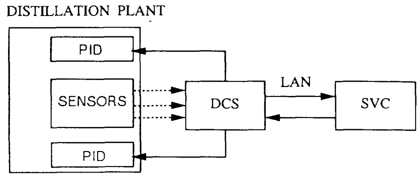

Fig. 4. Hierarchical control system for experiments

Table 1. Experimental conditions

Case 1		Case 2	
Initial state	Final state	Initial state	Final state
$D=11.4$ $x_D=0.77$	$D=12.5$ $x_D=0.765$	$D=11.1$ $x_D=0.857$	$D=12.5$ $x_D=0.851$

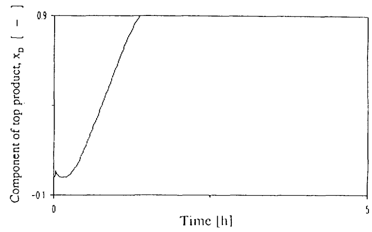

Fig. 5. Response profile of output in case 1

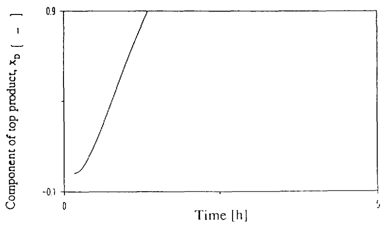

Fig. 6. A result of model fitting in case 1

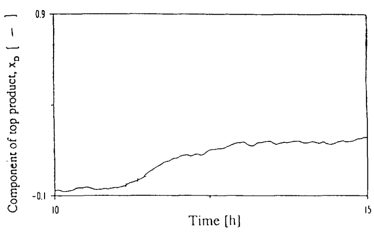

Fig. 7. Response profile of output in case 2

2.2. Results of modeling

Figures 5, 6, 7 and 8 show the results of step response experiments and modeling. Figures 5 and 7 show typical output response profiles measured in cases 1 and 2 respectively. These results were supplied to modeling. Figures 6 and 8 show the results of modeling in cases 1 and 2 respectively. In these figures the data of x_D are shown as the normalized scale. Simplex method was used for parameters estimation. These figures show that modeling was successfully carried out. **Table 2** shows the model paremeters of Eq. (1) identified in both cases. These values were used to design the fuzzy controller. The membership functions used in the experiments were shown in **Fig. 9**. The most popular trapezoid shape was adopted.

2.3 Regulatory control

Figure 10 shows a result of regulatory control in step change of the set-up value of the PID controller around 80% concentration of the ethanol product x_D, which is nearly the middle concentration between two models porperly acquired. The process value (PV) reached the changed set-up value (SV) smoothly after about 1 hour without drastic change of the manipu-

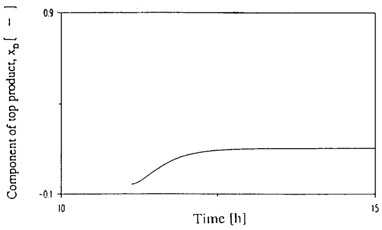

Fig. 8. A result of model fitting in case 2

Table 2. Results of model fitting

	K (mol(%)/(%))	T_1 (h)	T_2 (h)	τ (h)
Model 1 (Case 1)	24.49	1.816	1.895	0.0735
Model 2 (Case 2)	1.091	2.812	2.953	0.0735

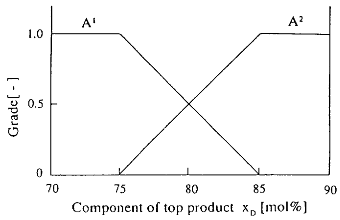

Fig. 9. Membership functions

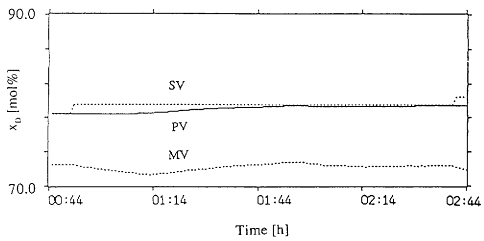

Fig. 10. A result of regulatory control

lated value (MV) given to the controlled valve. As the ethanol/water distillation system is an azeotropic system, it has been rather difficult to control in this concentration region in general. This result shows good control performance for this distillation system.

2.4 Tracking control

Some case studies on tracking control were carried out. **Figure 11** shows a result in the case of moving the operating point from 83.3% to 84.7% and then to 84.3%. The tracking control was successfully accomplished as PV followed the trajectory of SV (shown by stepwise line). This result suggested that the proposed tracking control system could work successfully in various cases of wide change in the operating point.

Conclusion

In this paper, a multi-model control algorithm using fuzzy rules is proposed and is applied to a regulatory and tracking control problem of the ethanol/water distillation system. According to the experimental results, the proposed method is expected to be a very effective method for non-linear process control. In this paper the transfer function model was adopted as the multiprocess model, but the representation form should not be resticted to this type, and we shall examine other forms, such as the ARX model.

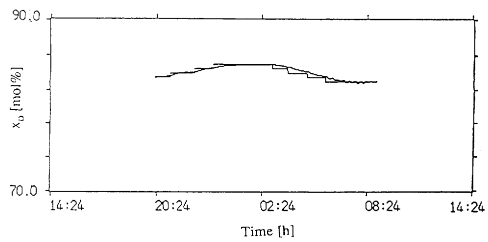

Fig. 11. A result of tracking control

Appendix

Kitamori's design algorithm based on partial knowledge of a process is formulated as follows. With this algorithm, the control parameters can be tuned so as the adjust a closed loop response to a desired reference response. The reference response is represented by Eq. (A1).

$$G_{\mathrm{ref}}(S) = 1/(\alpha_0 + \alpha_1\sigma S + \alpha_2\sigma^2 S + \cdots) \quad \text{(A1)}$$

where σ is the tuning parameter conrresponding to the rise time, and $\{\alpha_i\}$ are the parameters that statisfy the desired control performance. For example, he recommends the set of values $\{\alpha_i\}$ as follows:

$$\alpha_0 = \alpha_1 = 1\,, \quad \alpha_2 = 0.5\,, \quad \alpha_3 = 0.15\,, \quad \alpha_4 = 0.03, \cdots .$$

On the other hand, the general structure of the PID controller is given by Eq. (A2).

$$\begin{aligned} G_C(S) &= K_p(1 + 1/T_I S + T_D S) \\ &= (c_0 + c_1 S + c_2 S^2 + \cdots)/S \\ &= c_0(1/S + c_1/c_0 + S\cdot c_2/c_0) \quad \text{(A2)} \end{aligned}$$

Consequently, the closed-loop transfer function is given by Eq. (A3).

$$G^*(S) = 1/\left(1 + S\cdot\frac{a'_0 + a'_1 S + a'_2 S^2 + \cdots}{c_0 + c_1 S + c_2 S^2 + \cdots}\right) \quad \text{(A3)}$$

The control parameters can be obtained so as to make $G^*(S)$ coincide with $G_{ref}(S)$. In the case of PID action, the parameter σ can be obtained from Eq. (A4).

$$\begin{aligned} a'_3 - \sigma\alpha_2 a'_2 + \sigma^2((\alpha_2)^2 - \alpha_3)a'_1 - \sigma^3((\alpha_2)^3 \\ - 2\alpha_2\alpha_3 + \alpha_4)a'_0 = 0 \quad \text{(A4)} \end{aligned}$$

where σ should take the positive and minimum value of the solutions of Eq. (A4). The parameters c_0, c_1 and c_2 can be obtained by Eq. (A5).

$$c_0 = a'_0/\sigma\,, \quad c_1 = (a'_1 - \sigma\alpha_2 a'_0)/\sigma\,,$$

$$c_2 = \{a'_2 - \sigma\alpha_2 a'_1 + \sigma^2(\alpha_2{}^2 - \alpha_3)a'_0\}/\sigma \qquad \text{(A5)}$$

From Eqs. (A2), (A3) and (A5) we can calculated the parameters of the PID congroller, i.e., the proportional constant K_p, the integral time constant T_I and the derivative time T_D from Eq. (A6).

$$K_p = c_1\,, \quad T_I = 1/c_0\,, \quad T_D = c_2 \qquad \text{(A6)}$$

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Nomenclature

A	= fuzzy set	
a	= parameter of denominator series from transfer function	
B	= flow rate of bottom product	[l/h]
c	= parameter of denominator series from transfer function of a PID controller	
D	= flow rate of distillate	[l/h]
F	= flow rate of feed	[l/h]
$G(S)$	= Transfer function	
K_p	= proportional gain constant	[mol %/%(MV)]
L	= reflux flow rate	[l/h]
T_D	= differential time	[h]
T_I	= integral time	[h]
x_B	= conc. of volatile component in the bottom product	[mol%]
x_D	= conc. of volatile component in the top product	[mol%]
z_F	= conc. of volatile component in the feed	[mol%]
α	= parameter of denominator series form transfer function in Appendix	
ω	= truth value of the membership function	

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